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# Multiday Evaluation of Techniques for EMG Based Classification of Hand Motions

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***Abstract*— currently, most of the adopted myoelectric schemes for upper limb prostheses do not provide users with intuitive control. Higher accuracies have been reported using different classification algorithms but investigation on the reliability over time for these methods is very limited. In this study, we compared for the first time the longitudinal performance of selected state-of-the-art techniques for Electromyography (EMG) based classification of hand motions. Experiments were conducted on ten able-bodied and six transradial amputees for seven continuous days. Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Decision Trees (TREE) were compared. Comparative analysis showed that the ANN attained highest classification accuracy followed by LDA. Three-way repeated ANOVA test showed a significant difference (P<0.001) between EMG types (surface, intramuscular and combined), Days (1-7), classifiers and their interactions. Performance on last day was significantly better (P<0.05) than the first day for all classifiers and EMG types. Within-day classification error (WCE) across all subject and days in ANN was: surface (9.12 ± 7.38%), intramuscular (11.86±7.84%) and combined (6.11±7.46%). The between-day analysis in a leave-one-day-out fashion showed that ANN was the optimal classifier (surface (21.88 ± 4.14%) intramuscular (29.33 ± 2.58%) and combined (14.37 ± 3.10%)). Results indicate that that within day performances of classifiers may be similar but over time it may lead to a substantially different outcome. Furthermore, training ANN on multiple days might allow capturing time-dependent variability in the EMG signals and thus minimizing the necessity for daily system recalibration.**

*Index Terms*— **Electromyography; Pattern recognition; Classification; Myoelectric control; Prostheses; Intramuscular**

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## I. INTRODUCTION

Myoelectric control schemes use muscle contractions as control signals to activate prostheses [1]. During the contraction of muscles, the electric activity (Electromyography, EMG) is detected from selected residual limb muscles of an amputee [2]. Commercial myoelectric control systems employ the relatively simple approach of encoding the amplitude of the EMG signal measured at one or more sites to actuate one or more functions of a prosthesis [3]. Single-site controlled myoelectric devices are used when limited number of control sites (muscles) are available in a residual limb and utilize single electrode to control both motions of paired activity. Dual-site controlled myoelectric control scheme is commonly used in clinics in transradial amputees. This system utilizes separate electrodes for paired prosthetic activity from antagonistic muscles (i.e. wrist flexor and wrist extensor). When multiple degrees of freedom (DOF) are to be controlled, sequential and mode switches are used, allowing the same pair of electrodes to control a second DoF. Switching mode is performed by a brief co-contraction of the muscles or by a switch to toggle between different functions of a prosthesis. Although these control schemes are clinically and commercially viable option for myoelectric prostheses, they do not provide intuitive and simultaneous control of a device having multiple DOFs [3]. This, among other reasons, make patient compliance to the current prostheses low [4].

Pattern recognition (PR) schemes can be used to extract a wealth of controllable information from the EMG. The key assumptions of a PR myoelectric control are that repeatable and distinctive signal patterns can be extracted from muscle signals. These decoding algorithms have been used in academia for several decades [5,6]. Since then significant improvement has been made in these PR algorithms with the advent of advanced signal processing techniques and high-speed embedded controllers. These systems are intended to be more intuitive and control a greater number of DOFs which should improve performance while keeping the number of electrodes low. Furthermore, PR systems do not require independent channels, which can sometimes be impossible to locate due to small stump size.

In the context of PR of EMG signal, the first step involves feature extraction from the different time windows. Choosing a feature set is an important step as several studies [7] have shown some feature are more representative of data than others. These feature sets are then fed into the classifiers for the recognition of the different hand motions. The output of the classifier is used by the controller for the actuation of prosthetic devices. The typical modern classification algorithms used in myoelectric control are: Linear discriminant analysis(LDA) [8,9], Support vector machine(SVM) [10,11,12], K-nearest neighbour(KNN) [13], artificial Artificial Neural Network (ANN) [14-15], Bayesian classifiers [16], Gaussian mixture models [17], Fuzzy logic [18] and genetic algorithms [19]. It has been demonstrated in these studies that if proper methods are used, high classification accuracies (>95%) can be achieved on a dataset with multiple classes [20]. Despite these high accuracies, only one prosthetic control system based on pattern recognition is commercially available [21]. There are several factors which are preventing the implementation of these systems outside laboratory conditions, such as adaptation over time, muscle fatigue and electrode shift in offline settings [22,23,24].

The efficiency of classification algorithms is of utmost priority as prosthetic control is implemented on low performance embedded systems due to some constraints like the size of residual limb and space available in a socket. Many of these algorithms have been compared for short-term EMG recordings [25,26]. Englehart et al. compared the performances of LDA and MLP for four classes. LDA exhibited better a classification performance over MLP after using a PCA reduced feature set [27]. Kaufmann et al applied five PR schemes on 21 days of data from only one able-bodied subject to evaluate five classifiers (KNN, DT, MLP, LDA, SVM) and found that the accuracy degrades with increasing time difference between training and testing data, and drops gradually if not retrained for all algorithms but the LDA [28]. On the same data set, Phinyomark et al. found that LDA outperformed the rest of the seven compared classifiers with an overlapped window size of 500 ms and increment of 125 ms [29]. Bellingegni et al. evaluated the maximum acceptable complexity of each classifier, by using a constraint of a typically available memory of high-performance microcontroller [30]. It was found that a non-logistic regression (NLR) provided the best compromise between the complexity and the performance followed by multiple layer perceptron (MLP). Recently, it has been shown that classification accuracies vary significantly over time [31,32], as data recorded on one day has different characteristics from data recorded on the other day due to the real-world conditions mentioned above. The central question is: why studies have focused on comparing classifiers on the basis of their performance using short-term scenarios while many other factors such as time can influence their performances? Hence the choice of a classifier should not be entirely based on performance and computational load but on a trade-off between performance and robustness over time. Moreover, limitation of surface EMG suggests that combining a new control strategy by combining multiple channels from the surface and intramuscular EMG can increase the amount of information harvested from the body [33]. The combined effect of surface and intramuscular EMG could improve the performance of selected classifiers.

Weir et al. developed first implantable myoelectric sensors (IMES) for prosthesis control [34]. These electrodes were intended to detect and wirelessly transmit EMG signals to an electromechanical prosthetic hand via an electromagnetic coil built into the prosthetic socket. This system was only tested on animals. Since then only a few researchers have used IMES to achieve direct and simultaneous control of myoelectric prosthesis on humans. Such a control is not possible by using conventional surface-based myoelectric control [35,36,37]. The Myoelectric Implantable Recording Array (MIRA) is other solution for future advanced prostheses [38].

Intramuscular recordings have several advantages over surface EMG. The insertion of the intramuscular electrode can acquire signals from the small and deep muscles providing localized information, thereby greatly increasing the information to control a prosthetic device. Intramuscular recordings also have limited crosstalk and are less affected by factors such as skin impedance and precipitation [39], however, the selectivity of these recordings may constitute a drawback.

Therefore, the aim of this study was to evaluate and compare for the first time the longitudinal performance of five classifiers; Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN), Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbour (KNN) and Decision Trees (TREE) over seven days for surface and intramuscular EMG recordings. The intention was to provide insight into the behavior of the selected classifiers with time as a robustness factor, an experimental design that constitutes the novelty of this study. Intramuscular EMG signals was recorded concurrently in an effort to increase the information content. Intramuscular electrodes were kept inside the muscles for seven days in ten able-bodied and six trans-radial amputee subjects.

The rest of the paper is prepared as follows: in the next section, the subjects, data collection, and experimental procedure are presented. In Section III complete experimental results with respect to different training and testing strategies are presented. In Section IV, a discussion is given on the impact of the use of surface and intramuscular recordings and classification methods. Finally, the conclusions are given in Section V.

## II. EXPERIMENTAL METHODS

### *A. Subjects*

Subjects were divided into two groups, one group

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comprised of eight subjects who had transradial amputation at different levels (all males, age range: 20-56 yrs., mean age 26.56 yrs.) and the other group included 10 normally-limbed subjects who had no history of upper extremity deformity or other musculoskeletal disorders (all male, age range: 18-38 yrs., mean age 24.6 yrs.). Subjects were informed about the experiment and their participation was voluntary. They provided informed written consent and they had the right to leave the experiment without providing an explanation. Out of the eight inducted amputees, two left the experiment (after first and third day) before the completion of data collection and thus were excluded from data analysis. The procedures were in accordance with the Declaration of Helsinki and approved by the Aalborg University, Denmark local ethical committee approval number N-20160021.

### B. Data Collection

EMG signals for 11 different motions were recorded from the skin surface as well as from inside the muscles. Surface EMG was recorded using bipolar Ag/AgCl electrodes (Ambu WhiteSensor 0415M). According to the surface area available on the residual limb, five to six surface bipolar electrodes were placed at equal distance from each other around the circumference of the forearm. Positions of surface electrodes were marked each day with a skin maker, to ensure correct placement of electrodes on the following day. Three to six bipolar wire electrodes were used to record intramuscular EMG. These electrodes were inserted to reside underneath each surface EMG electrode pair, providing similar sites for surface EMG so intramuscular EMG could be recorded together with the surface EMG. Intramuscular electrodes in amputees were inserted using a B-mode ultrasound machine, whereas in healthy subjects, we relied on surface anatomy of the forearm for insertion.

Intramuscular wire electrodes were made of Teflon-coated stainless steel (A-M Systems, Carlsborg WA diameter 50µm) and were inserted into each muscle with a sterilized 25-gauge hypodermic needle. Antiseptic measures were used to minimize the risk of infection. Skin of subjects was prepared by using 70% isopropyl alcohol before inserting the needle. All the electrodes used were sterile and unpacking of needle and electrodes took place using sterile gloves. The needle was inserted to a depth of approximately 10-15 millimetres below the muscle fascia and then removed to leave the wire electrodes inside the muscle. The insulated wires were cut to expose 3mm of wire from the tip to maximize pickup area [40]. Intramuscular electrodes were kept inside the muscles for seven days while surface EMG electrodes were placed on a daily basis on the same location, with the help of the marks placed on the skin on the previous day.

After the electrodes had been inserted, a sterile bandage was placed to cover all the insertion sites and only the tips of the wires were left outside the bandage to allow connection to the amplifiers. After each session, a second bandage was placed to cover the wires before the subject could leave the room, to minimize the risk of electrode displacement. The top bandage was removed to allow wire connections at the subsequent session. The bottom bandage was only removed after the completion of all sessions or if the subject wished to withdraw from the experiment.

EMG signals were acquired using a commercial myoelectric amplifier (AnEMG12, OT Bioelletronica, Torino, Italy). Signals were analog bandpass filtered (10 – 500 Hz for surface EMG and 100 – 4400 Hz for intramuscular EMG), A/D converted using 16 bits (NI-DAQ PCI-6221), and sampled at 8 kHz. Recorded signals were amplified with the gain of 2000 for surface and 5000 for intramuscular EMG. A reference wristband electrode was placed on the opposite hand close to the carpus.

### C. Experimental Procedures

Subjects were prompted to execute comfortable and sustainable contractions corresponding to 11 classes containing 10 active motions: Hand Open (HO), Hand Close (HC), Wrist Flexion (WF), Wrist Extension(WE), Pronation,(PRO) Supination(SUP), Side Grip (SG) (all fingers are flexed around the object which is usually at a right angle to the forearm and thumb is wrapped around the object), Fine Grip (FG) (Metacarpophalangeal and proximal inter-phalangeal joint of the fingers are flexed, thumb is abducted and the distal joints of both are extended, bringing the pad of the thumb and finger together), Agree (AG) (thumb abducted and fingers flexed, with thumb pointing in upward direction), Pointer Grip (PG)(index finger is extended while middle, ring, and little fingers are flexed, with the thumb in adducted position) and Resting state or no motions (RT).

For data collection, BioPatRec [41], an open source acquisition software was used. Data of four repetitions of five seconds each were collected. One experimental session was conducted in one day. The complete duration of the experimental session was around one hour. The time interval between two experimental sessions on consecutive days was approximately 24 hours. The amputee subjects had never used a prosthesis, except for one subject who had been using a body-powered prosthesis. Experimental sessions were conducted for seven consecutive days.

During the experiment, over the course of seven days, some of the intramuscular electrodes were pulled out. In amputee subjects, about three electrodes remained in the muscles and functioned properly for seven days. In normally limbed subjects, at minimum four intramuscular electrodes remained inside muscles until day seven. Thus, data from only functioning electrodes were used for analysis. The number of surface channels used for analysis was reduced accordingly on a per subject basis to allow a fair comparison. Although absolute classification rates will be reduced by eliminating channels, the time effect on classification, the key element of this study, is the essential observation. Therefore, the number of viable channels can be considered a subject-specific parameter, and

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consequently is embedded in the *subject* effect in the statistical analysis.

### *D. Data Analysis*

EMG surface signals were digitally high-pass filtered (third order Butterworth filtered) with a cut-off frequency of 20 Hz as well as low pass filtered with a cut-off frequency of 500 Hz. A notch filter at 50 Hz was used to reduce power line interferences. Intramuscular EMG signals were digitally high-pass filtered (third order Butterworth filtered) with a cut-off frequency of 100 Hz and low-pass filtered with a cut-off frequency of 1500 Hz. From every five seconds of contraction time, one second was provided for onset phase and one second for offset phase to avoid non-stationarity. Subsequently, three seconds of the steady-state phase was used for the extraction of features. Seven time-domain features were extracted from incrementing (by 35 ms) windows of 160 ms duration. These features were Mean Absolute Value (MAV), Zero Crossings (ZC), Slope Sign Changes (SSC), Willison Amplitude (WAMP), Waveform Length (WL), Myopulse Rate (MYOP) and Cardinality (CARD).

Data with high dimensionality tend to be prone to overfitting and loss of information as an overfitted model can lead to classification errors [42]. PCA was used to overcome the curse of dimensionality. The classification error (ratio between misclassification and total classification) was used as a performance index. Within-day classification error (WCE) was defined as training and testing data on the same day. Four-fold cross-validation was used to quantify WCE. Each fold comprised of assigning one repetition of testing data and the remaining three repetitions as training data; the mean of the four classification errors was reported. To investigate the long-term effects on classification performance, classification between days was computed on the corresponding seven days of data collection. Between-day classification error (BCE) was defined as training and testing data from two different days. BCE was quantified using a 7-fold validation procedure where six days were used for training and one day for testing. This was repeated seven times and the results were averaged.

The analysis was carried out on each EMG type (surface and intramuscular) and their combination. Feature vector from training data was transformed into lower-dimensional subspace by application of principal component analysis which has an effect of linearizing the discrimination tasks of the classifier. Principal components contributing to 99% variance, were used for classification purposes. To assign the number of neurons used in the hidden layer of the Artificial Neural Network, a comparison of the classification error was performed. The classification error was therefore compared to each subject with different numbers of neurons going from 2 to 15. The net architecture with highest classification accuracy was selected. To implement K-NN, several architectures were implemented, varying the number of neighbours from 1 to 15 (only the odd numbers). The criterion to select the optimal K-NN configuration was the mean classification error. The net architecture with highest classification accuracy was selected.

### *E. Statistical Analysis*

For overall performance based on classification accuracies, a three-way repeated analysis of variance (ANOVA) with factors signal types (surface, intramuscular and combined), Days (1-7) and Classifiers (TREE, NB, KNN, SVM, LDA, and ANN) was used for comparison. A two-way ANOVA was used to compare between within a day classification error (WCE) and between days classification error for the best performing classifier that was ANN. P-values less than 0.05 were considered significant.

## III. RESULTS

### *A. Feature Space with principal components*

Figure 1 showed the geometrical changes in feature space for first two principal components of three classes (Pronation, Supination, and Fine Grip) on day one, three, five and seven in one amputee subject. Three classes were used to exhibit changes in the genetic distance between populations in 2-dimensional embedding over time. PCA transformation ensures horizontal axis PC1 has the most variation, vertical axis PC2 the second most. Factor scores for both components improved over time distinctly for all classes till days seven. On the first, a cloud of data (Pronation, Supination and Fine Grip) could be seen. Genetic distances between populations also increased by day seven as three classes could be seen as individual class showing adaptation of subject over time.

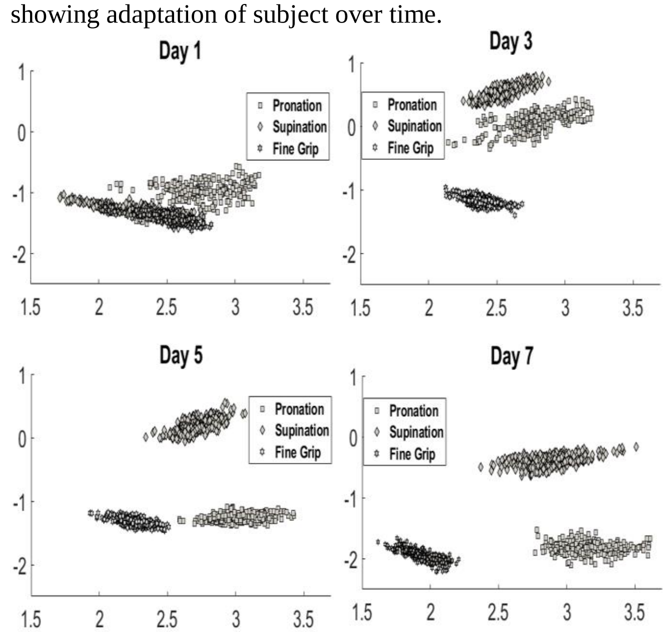


**Figure 1.** Surface EMG feature space representing two principal components for three classes Pronation '□', Supination '◊' and Fine Grip '*' in an amputee.

### *B. Within-Day Comparison*

Three-way repeated ANOVA test showed significant difference (P<0.001) between EMG types (surface, intramuscular and combined), Days (1-7), classifiers

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(TREE, LDA, SVM, NB, KNN, ANN) and their interactions ([Days*classifier], [Days*Type], [Type*Classifiers] in able-bodied and amputees.

**Classifiers:** In amputees, no significant difference (95% of CI [-1.52 0.23], [-0.75 1.00], [-0.10 1.65], P = 0.27, 0.99, 0.11) was found between KNN, SVM and NB. The remaining classifiers were significantly different from each other. ANN was best and TREE was the worst on (95% of CI [20.60 22.35], P < 0.01). In able-bodied, no significant difference (95% of CI [-0.83 0.31], P = 0.75) was found between NB and SVM. The remaining classifiers were significantly different from each other. ANN performed best and TREE performed worst (95% of CI [14.90 16.05], P < 0.01). **Days:** In amputees, all days were significantly different (P < 0.01) from each other except Day 2 and Day 4 (95% of CI [-0.1.32 0.64], P = 0.94). Day 7 was significantly better P<0.01 than rest of the days.

In able-bodied, day five, six and seven were significantly different from all other days. Day 2 and Day 3 found no significance between each other (95% of CI [-0.69 0.58], P = 0.94). Day 7 was significantly better than Day 1 (95% of CI [7.22 9.19], P ≤ 0.01)

Interactions between each factor (type*days), (type*classifiers) and (days*classifiers) found that type (combined ANN), day (seven) and classifier (ANN) was statistically better (P ≤ 0.01) than any other type, day and classifier in amputees and able-bodied.

*1) Surface EMG*

The results of WCE across amputees and able-bodied with surface EMG are summarized in Figure 2. Each group represents the performance of all classifiers on each day for seven consecutive days. On average, for all classifiers, WCE reduced consistently for seven consecutive days.

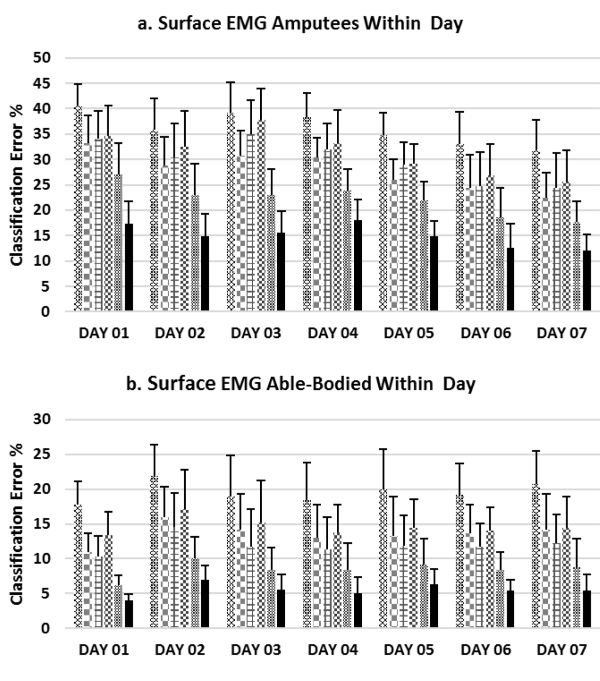


**Figure 2.** Mean classification error averaged across a. Amputees and b. Able-bodied subjects with surface EMG for all classifiers (Decision Tree, Naïve Bayes, K-Nearest Neighbour, Support Vector Machine, Linear Discriminant Analysis, Artificial Neural Network) within a day.

Multiple comparisons revealed all classifiers were significantly (P<0.05) better than Decision trees in both amputees and able-bodied (WCE (40.76 ± 4.01%, 17.83 ± 3.22%) on the first day, (32.03 ± 5.74 %, 20.71 ± 4.78 %) on the seventh day) respectively.

In amputees, ANN outperformed (P<0.05) rest of the classifiers with error decreasing consistently until day seven to 12.07 ± 3.17 %. No significant difference (P = 0.32) was found between KNN and SVM. A similar effect (P = 0.08) was seen between KNN and NB. Overall LDA and ANN showed a change of 9.31 % and 5.32 % respectively till the seventh day.

In able-bodied subjects, LDA and ANN outperformed (P<0.05) rest of the classifiers with error decreasing consistently until day seven to 8.81 ± 4.05 % and 5.43 ± 2.37 %. No significant difference (P = 0.15) was found between KNN and SVM. Classification accuracy improved over time as Day 6 and 7 were significantly better than day one to four.

*2) Intramuscular EMG*

Figure 3 shows the changes in WCE over seven days using intramuscular EMG for all subjects (able-bodied and amputees). In amputees, Day 7 was significantly better (P<0.05) than rest of the days implying learning and stabilization of the implanted electrodes. ANN outperformed (P<0.05) all other classifiers with WCE 14.15 ± 4.54 % on the seventh day. Overall LDA and ANN showed a change of 10.45 % and 5.83 % respectively till the seventh day.

In able-bodied, ANN outperformed (P<0.05) rest of the classifiers with 7.95 ± 2.27 % error till the seventh day. All classifiers were significantly different from each other

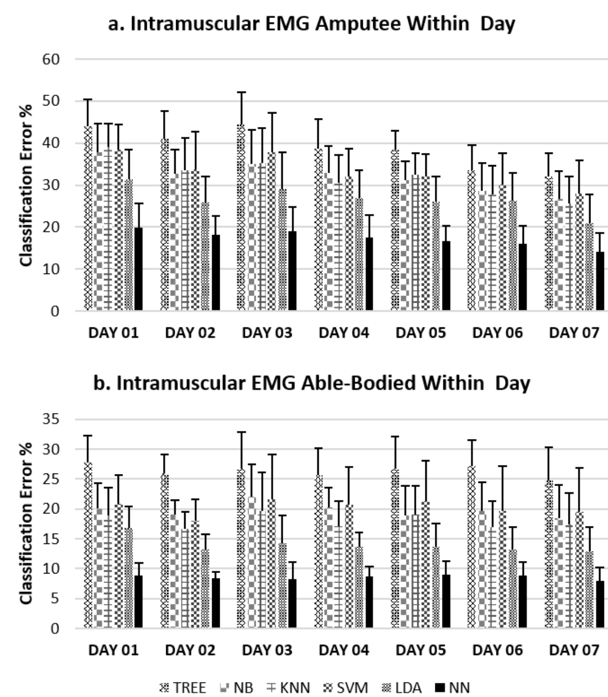

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**Figure 3.** Mean classification error averaged across a. Amputees and b. Able-bodied subjects with intramuscular EMG for all classifiers (Decision Tree, Naïve Bayes, K-Nearest Neighbour, Support Vector Machine, Linear Discriminant Analysis, Artificial Neural Network) within a day.

(P<0.05) expect SVM and NB (P = 0.86). Day 7 was significantly better (P<0.05) than Day 1. No significance difference (P = 0.97, 0.62, 0.92) was found between Day 4, 5 and 6.

*3) Combined EMG*

In combined EMG, attributes from the surface and intramuscular EMG were combined to analyse the overall change in performance of different classifiers (Figure 4). By combining the attributes, significant improvement in WCE performance was seen in all classifiers with respect to the surface and intramuscular.

In amputees, ANN outperformed (P<0.05) rest of the classifiers as error reduced to 7.44 ± 3.17 % until the seventh day from 11.70 ± 4.41 % on the first day. No significant difference (P = 0.98, 0.63, 0.24) in performance was observed between KNN (14.91 ± 6.99%), SVM (14.32 ± 6.26 %) and NB (16.77 ± 5.05%). Overall KNN, SVM, and NB showed a change of 14.01 %, 14.32 %, and 12.7 % respectively until the seventh day. Day 7 was significantly better (P<0.05) than rest of the days except Day 6 (P = 0.20).

In able-bodied, ANN in combined EMG outperformed all the classifiers implemented (P<0.05) with lowest classification error 3.47 ± 1.52% until the seventh day. WCE for day five, six and seven were significantly (P<0.05) better than day two and three. Table 1 represents the average WCE for able-bodied and amputees.

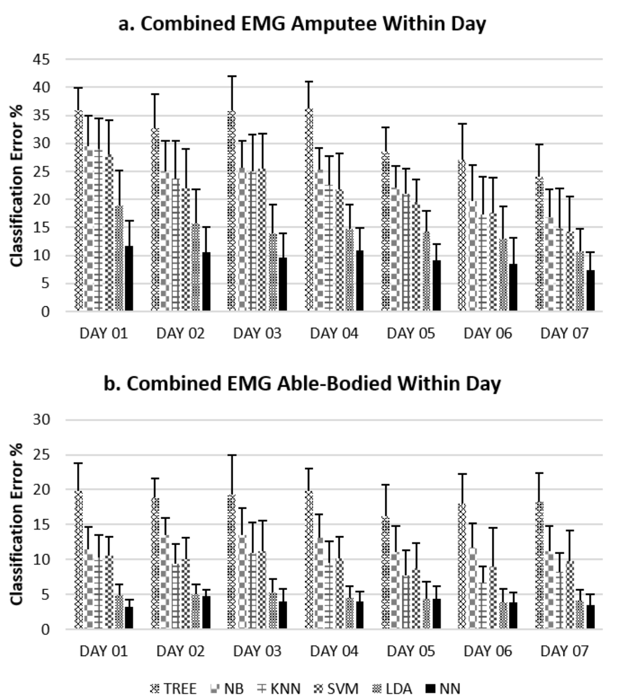


**Figure 4.** Mean classification error averaged across a. Amputees and b. Able-bodied subjects with combined EMG for all classifiers (Decision Tree, Naïve Bayes, K-Nearest Neighbour, Support Vector Machine, Linear Discriminant Analysis, Artificial Neural Network) within a day.

**Table 1.** Average classification errors for seven days across all subjects.

| **ABLE-BODIED** | | | |
|---|---|---|---|
| | **SURFACE** | **INTRAMUSCULAR** | **COMBINED** |
| **TREE** | 19.55±4.94 | 26.36±6.63 | 18.60±5.56 |
| **NB** | 13.61±4.22 | 19.75±6.43 | 12.24±4.26 |
| **KNN** | 11.98±4.29 | 17.99±6.32 | 8.96±3.96 |
| **SVM** | 14.63±4.16 | 20.23±6.69 | 9.95±3.74 |
| **LDA** | 8.468±3.74 | 13.96±5.52 | 4.59±2.59 |
| **ANN** | 5.55±2.21 | 8.578±2.29 | 3.95±1.88 |
| **AMPUTEES** | | | |
| | **SURFACE** | **INTRAMUSCULAR** | **COMBINED** |
| **TREE** | 36.27±5.28 | 38.86±7.00 | 31.44±6.31 |
| **NB** | 27.99±5.16 | 32.14±7.21 | 23.41±5.74 |
| **KNN** | 29.94±5.54 | 32.04±7.58 | 21.95±6.58 |
| **SVM** | 31.39±5.86 | 33.18±7.75 | 21.29±6.10 |
| **LDA** | 22.13±4.86 | 26.64±6.43 | 14.49±4.46 |
| **ANN** | 15.08±3.59 | 17.35±4.85 | 9.70±2.63 |

Figure 5 depicts a representative average performance (LDA) for a poor amputee subject (top plot) with three inserted wires and a good amputee subject (bottom plot) with six inserted wires. It can be seen that certain classes (from the poor subject) were affected due to absence of electrodes in the anatomical position related to flexor muscles.

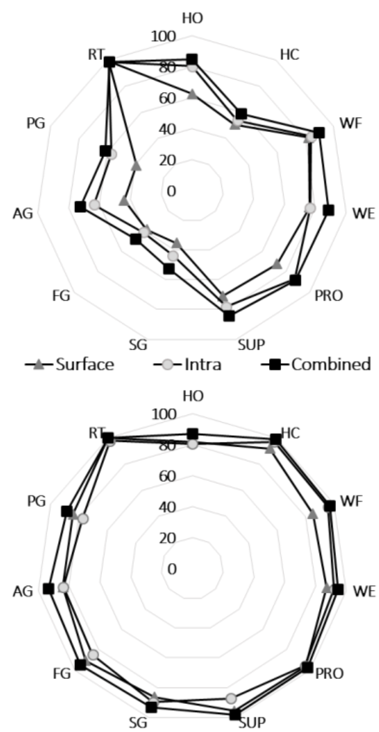


Figure 5. Class performance for a poor amputee subject (top) with three inserted wires and a good amputee subject (bottom) with six inserted wires using linear discriminant analysis. Performance is given for surface (Δ), intramuscular (○) and combined EMG (□).

## B. Between Days Comparison

For overall performance based on BCE (Figure 6 a, b), two-way repeated measures analysis of variance (ANOVA) with factors EMG signal types (surface, Intramuscular and combined) and Classifiers, showed that combined EMG is significantly (P<0.001) better than the surface and intramuscular EMG. ANN was still the best classifier and its performance was (P<0.001) significantly better than the rest of the classifiers and TREE was the worst one. LDA was the second-best classifier significantly better than KNN, NB, and TREE.

*1) Surface EMG*

To investigate changes in signal characteristics during the 7-day experiment and its effect on pattern recognition based control algorithms, all possible combinations between days were analyzed. Figure 6 represents all possible combinations of BCE for surface and intramuscular EMG for seven functional motions in amputees and able-bodied. BCE for both surface and intramuscular EMG improved along the course of the experiment. For surface EMG, a classifier trained on the data from the first day and tested on the data from the second day showed BCE of 23.8% which reduced to 14.4% when the classifier was trained on the data from the sixth day and tested on the data from the seventh day. Results indicated that performance continuously improved for the system trained on the previous day and tested on the next day, indicated by the outlined cells. BCE in surface EMG reduced to (33.23 ± 8.27 % in amputees and 10.54 ± 0.69 % in able-bodied) for the classifier trained on the sixth day and tested on the seventh day.

*2) Intramuscular EMG*

On average across all classifiers, the performance of intramuscular EMG was lower than surface EMG. Performance of ANN was significantly better ($P<0.05$) than rest of the classifiers. LDA was the second-best classifier significantly better ($P<0.05$) than TREE and NB in both amputees and able-bodied.

In amputees, no significant difference (95% of CI [-3.09 8.60], P = 0.70) was found between TREE and NB. Similarly, no significance was revealed in the comparison of KNN and SVM (95% of CI [-2.98 8.71], P = 0.67).

*3) Combined EMG*

For the combined features from the surface and intramuscular EMG, improvement in BCE performance was observed in all classifiers except TREE with respect to the surface and intramuscular. Performance of ANN (22.06 ± 2.25% in amputees, 6.68 ± 0.82 % in able-bodied) was significantly better ($P<0.05$) than rest of the classifiers. Combined EMG showed improved BCE on LDA as it was significantly better ($P<0.05$) than SVM, KNN, NB, and TREE in amputees and able-bodied. Combined BCE which outperformed both surface and intramuscular BCE and reduced to (22.05 ± 2.25 % in amputees and 6.68 ± 0.82 % in able-bodied) for the classifier trained on the sixth day and tested on the seventh day.

In amputees, KNN was significantly better ($P<0.05$) than TREE but not different from NB (95% of CI [-5.40 8.34], P = 0.98) and SVM ((95% of CI [-4.71 9.04], P = 0.92).

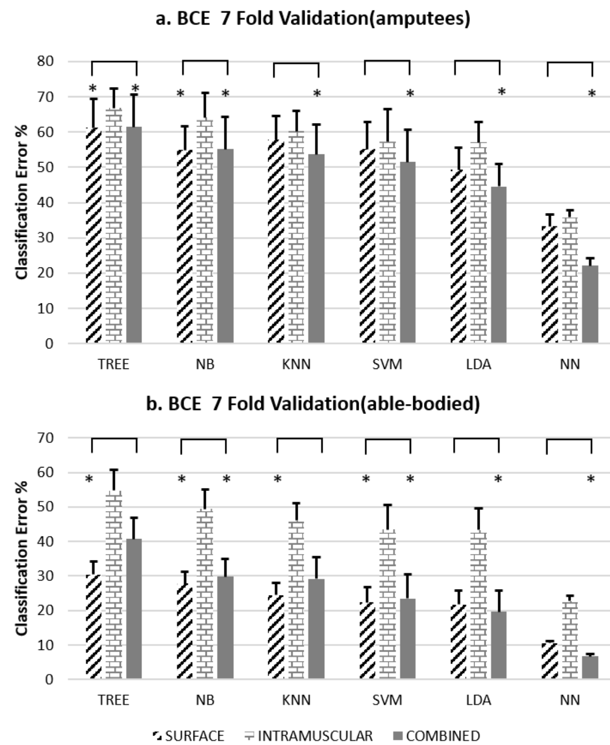


**Figure 6.** Changes in BCE (a. Amputees, b. Able-bodied) for all classifiers (Decision Tree, Naïve Bayes, K-Nearest Neighbour, Support Vector Machine, Linear Discriminant Analysis and Artificial Neural Network) and all type (surface, intramuscular and combined EMG). Significant difference in types is represented by '*'.

## IV. DISCUSSION

There is an extensive discussion in the literature about performance of classifiers, with each having variable number of amputees (trans-radial [43] or trans-humeral [44], feature selection methods [45,46,47], features (Time Domain [46, 48, 49], Frequency Domain [50, 51, 52] and Time-Frequency Domain [53,27]), feature reduction techniques [54, 20], classification parameters (no. Of neurons, no of neighbours) [8,9,12,20,27] and number of recruited subjects (healthy and amputees)[8,9,12]. But one fundamental missing factor in these studies is their performance over time for long-term usability assessment. In this study, Classification performance of most adopted classifiers for surface and intramuscular EMG signals were evaluated for seven days and showed that within day performances of classifiers may be similar but over time it may lead to a substantially different outcome. Results have indicated that subjects with upper limb amputation and able-bodied subjects can learn to produce discriminative contractions which improved on successive days of training and testing. Performance of classifiers varies within-day and between days. For within day classification error (WCE), ANN performed significantly ($P<0.05$) better than all other tested classifiers and its performance improved over time. LDA is the most recommended classifier in the literature and accuracies up to 98% are reported in able-bodied subjects for surface recording [20, 27, 49]. Accuracies in LDA method were obtained up to 96.1% per day for surface

EMG. TREE was the worst classifier with average classification error of 19.55% (Figure 4), previous studies reported low performance up to 30% classification error [55]. In general, the performance of each classifier was similar to previously reported results [53, 56].

Combined EMG was significantly better (P<0.05) than the surface and intramuscular EMG as a combined feature set improved the information level from muscles containing both local and global content. By using implantable electrodes, signals from deep muscles can be extracted which otherwise are not accessible or attenuated for surface EMG. This is in agreement with [34] where it was shown that intramuscular and surface EMG have complementary information.

Intramuscular signals provide independent control sites that can enable simultaneous and proportional control of multiple DOF's [56]. The downside of this simultaneous and proportional control is past pointing, isolating 1 DOF targets and ballistic nature of movements during positioning [56,57]. Since both acquisition types (surface and intramuscular) and their control schemes (sequential and simultaneous) have limitations, a control scheme based on both surface (isolate single DOF) and intramuscular (provide simultaneous and proportional control of multiple DOF's) recordings could be devised for providing faster, intuitive and natural control. The main drawback of such implantable system would be the risk of infection and securing stable position for electrodes over a longer period. Wireless implantable systems [34,38] could be one of the solutions to ensure stable and secure electrodes in deep and superficial muscles. In the effort to mitigate the problems related to wireless technology, an gateway using osseo-integration has been proposed for long-term motor control of artificial limbs [58].

As the performance of amputees continuously improved with time, we anticipate that it may have improved further if the duration of the experiment was increased. The trend of improvement for WCE in able-bodied subjects for all EMG types (surface, intramuscular and combined EMG) was similar to amputees; though the error rate was higher in amputee subjects (Table1). The consistent improvement in the performance (WCE) also describes the improvement in the learning ability or the adaptation of the subjects. A daily calibration of the system will still be needed for surface or intramuscular EMG recordings because the BCE was higher than WCE.

The poor performance between days has been one of the main challenges in the long-term use of pattern recognition based myoelectric prostheses [31]. Variations in BCE were analyzed by maximizing the amount of training data without including any data from a testing day in a leave-one-day-out fashion. It was found that ANN performed best in comparison to the other classifiers (Figure 6) for all EMG types (surface, intramuscular and combined). The comparison of BCE and WCE for the optimum classifier (ANN) revealed that increasing the amount of training data can significantly reduce BCE and might converge to WCE, however, this may require the use of deep networks as provided by deep learning architectures. The decrease in the BCE performance implies that EMG characteristics change and same motions may become uncorrelated over time leading to the need to recalibrate or retrain the classifier. Nevertheless, we expect that training a network classifier on multiple days will enable the possibility to capture the EMG variabilities of each motion and thereby limit the necessity for system recalibration.

It should be noted that classifiers were compared for only an offline PR based myoelectric control system and it is not known how well these algorithms would perform in real-time scenarios. Offline performance measures have been challenged in many studies and the consensus is that they do not provide a realistic measure of usability [59,60,61]. Future work would focus on the long-term real-time testing including simultaneous and proportional control. Real-time control using invasive EMG is feasible as already demonstrated by others [57,62,63]. One major factor about the performance of intramuscular is related to the use of wire electrodes connected at the skin surface to the amplifier. This is a limitation that may signify to generalize with care our results to all implantable systems. First, this configuration caused wires to be pulled out and second, displacements in the implanted depth may have changed due to the pulling force of connecting cables. Therefore, we cannot guarantee that the implanted electrodes were measuring from the same area throughout the seven days of the experiments. This is a limitation that is worth mentioning because the results of future studies could be different. An efficient way of testing such system would be to use wireless implantable sensors, but to date, they are not commercially available. Considering the specificity of the intramuscular channels, the reduction in the number of channels can result in poor classification performance for certain classes. As shown in Figure 5, certain classes were affected due to absence of electrodes in that anatomical location. However, it should also be useful to note that the removal of the surface EMG channels that correspond to the failed intramuscular EMG channels causes a correlated decrease in performance on the same classes. The overarching point however, is that while the absence of certain channels may be problematic in classifying specific classes, this does not detract from the focus of this experiment: the observation of the temporal effect upon performance.

## V. CONCLUSION

The study presented a comparison of classification algorithms using surface and intramuscular EMG signals for myoelectric control of upper limb prosthesis. Within-day performances in literature showed the near-perfect performance of these algorithms 95% to 98%. Paper investigated the behavior of the machine learning algorithms for longer periods with different training schemes of data. Significant differences were found attributing differences in each adopted classifier. Results showed that a classifier having deep architecture is robust over time.

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